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Graph isomorphism + Gabor wavelet for face Recognition

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Abstract-*This paper presents an innovative face recognition method which is based on combination of graph isomorphism technique and Gabor wavelet. Here features are selected. Then algorithm determines the distance between these features in the face image. The algorithm applies Gabor wavelet on the selected features. Algorithm takes into account Gabor coefficient as well as Euclidean distance between features for face recognition. Brightness normalized and non-normalized face images are given for face recognition to demonstrate that the normalized faces can improve the recognition rate.*

Keywords- Face detection, graph isomorphism, Face recognition, brightness normalization, Gabor wavelet.

I. INTRODUCTION

The choice of the object representation is crucial for an effective performance of cognitive tasks such as object recognition, fixation, etc. Face recognition is an example of advanced object recognition. In this paper we demonstrate the use of Gabor wavelets and graph isomorphism for efficient face recognition. Face recognition is influenced by several factors such as shape, reflectance, pose, occlusion and illumination which make it even more difficult. Many brightness normalization algorithms have been presented before [1, 2, 3, and 4]. But they are computationally expensive. Paper introduces the simple preprocessing technique such as brightness normalization to improve face recognition rate. Paper wants to introduce combination of Gabor wavelets and graph isomorphism for an efficient face recognition system simulating human perception of objects and faces. A face recognition system could greatly aid in the process of searching and classifying a face database and at a higher level help in identification of possible threats to security. The purpose of this study is to demonstrate that it is technically feasible to scan pictures of human faces and compare them with ID photos hosted in a centralized database using combination of Gabor wavelets and graph isomorphism. The objective of the face normalization is to reduce the effect of useless, interferential and redundant information such as background so as to enhance the recognition process. . Paper proposes 2 algorithms of face recognition. First graph isomorphism and second combination of graph isomorphism and Gabor wavelet. Algorithm assumes that the face is already detected. Then manually select features such as left eye ball center and right eye ball center, nose tip and left and right corners of the mouth. Graph isomorphism finds Euclidean distance between features for face recognition. Graph isomorphism + Gabor wavelet algorithm takes Gabor representation of face image. Now along with Gabor coefficient take Euclidean distance between features as well for face recognition. Compare result of two proposed algorithms. The experiments carried out showed that the proposed algorithm can effectively and efficiently recognize the face images. The experiments showed that after the brightness normalization the face recognition rate was improved by about 4 to5 percent for the combined method on the ORL face image database.

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II. ALGORITHM

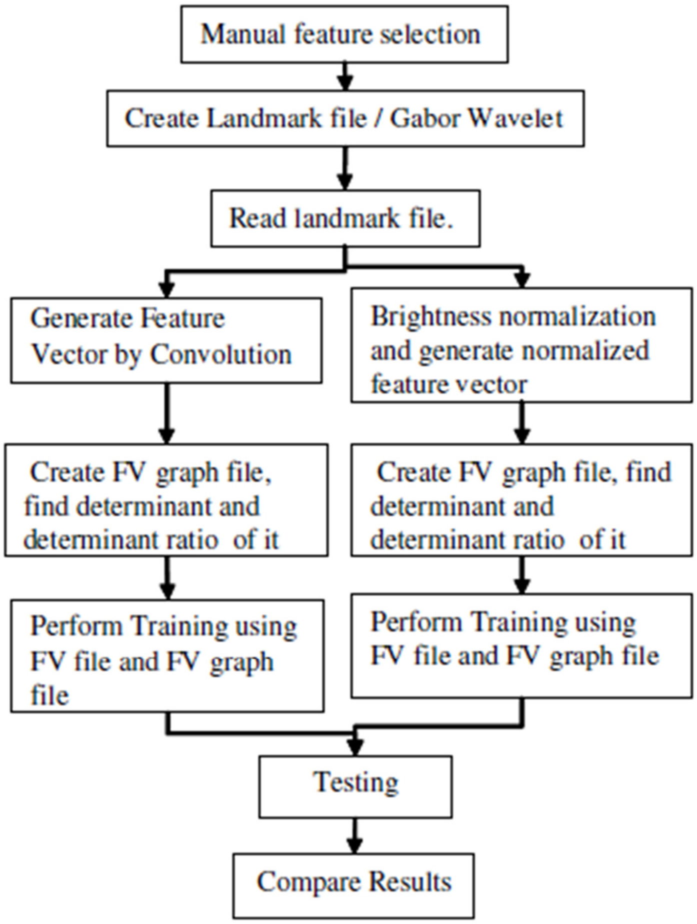

Figure 1 flowchart of the combined face recognition algorithm.

III. FACE GRAPH CREATION & GRAPH ISOMORPHISM

All 5 features (left eye ball and right eye ball center, nose tip and left and right corners of mouth) are manually selected and their coordinates(x,y) are stored in a file called landmarks DB. Connect these five features by lines tread landmark file. Brightness normalization and generate normalized feature vector Testing Compare Results Create FV graph file, find determinant and determinant ratio of it Perform Training using file and FV graph file Perform Training using FV file and FV graph file Create FV graph file, find determinant and determinant ratio of it Create Landmark file / Gabor Wavelet Manual feature selection Generate Feature Vector by Convolution each other and graph is form called face graph. Create adjacency matrix called graph file FV_graph_file to store Euclidean distance between these graph points/nodes. The distance of point from itself is taken as 0. Graph isomorphism technique is used for face recognition. Is means same and morphism means structure. Algorithm compares 2 face graph to check whether they are having same structure.

IV. GABOR WAVELET AND BUNCH GRAPH CREATION

The Gabor Transform is one of the most famous image processing tools that is used to capture spatial and orientation details [5, 6]. The Gabor wavelet representation facilitates recognition without correspondence because it captures the local structure corresponding to spatial frequency, spatial localization, and orientation selectivity. As a result, the Gabor wavelet representation of face images should be robust to variations due to illumination and facial expression changes.

The Gabor wavelet is used here in order to obtain a "Gabor representation" of the image that can hopefully capture class-specific information that will help enhance recognition rates. The representation of images by Gabor wavelets is chosen for its biological relevance and technical properties. The Gabor wavelet approach is fundamentally different from others because it recognizes faces by comparing their parts instead of performing Holistic image matching. The features are represented by Gabor jets. The jets are extracted from images with manually selected landmark locations. The model jets are then collected in a data structure called bunch graph. The bunch graph has a node for every landmark on the face. Every node is a collection of model jets for the corresponding landmark. The bunch graph serves as a database of landmark descriptions that can be used to locate landmarks in novel imagery. The algorithm first finds landmark locations on the images that correspond to facial features such as the eyes, nose, and mouth. It then uses Gabor wavelet convolutions at these points to describe the features of the landmark. A face graph is used to represent each image. The face graph nodes are placed at the landmark locations, and each node contains a Gabor jet extracted from that location. The similarity of two images is a function of the corresponding face graphs. Novel jet contains frequency information about the local image region around their extraction point. The landmarks are characterized by two things, a location in the image and a Gabor jet extracted from that location. After the face graphics created, the image is discarded, and the face graph becomes the internal representation of that image. The face graph occupies less memory than the image, and computing the similarity of face graphs is much faster than computing the similarity of images. For this reason, an entire database of faces can be kept in memory, and new images can be identified rapidly. The algorithm performs the wavelet convolution using pre computed wavelet masks. Each mask is a two dimensional array that is used as a lookup table for wavelet values during convolution. The masks are centered over the correct location in the image, and each corresponding value is multiplied and added to the sum. To compute both the real and imaginary part of the wavelet, it is necessary to convolve the image with two masks that are out of phase by p /2, corresponding to the use of sine and cosine in the wavelet transform.

There are five parameters that control the wavelet.

1 q specifies the orientation of the wavelet. This parameter rotates the wavelet about its center. The orientation of the wavelets dictates the angle of the edges or bars for which the wavelet will respond.

2 l .specifies the wavelength of the cosine wave, or inversely the frequency of the wavelet. Wavelets with a large wavelength will respond to gradual changes in intensity in the image.

3._ Specifies the phase of the sinusoid. Typically Gabor wavelets are based on a sine or cosine wave. In case of this algorithm, cosine wavelets are thought to be the real part of the wavelet and the sine wavelets are thought to be the imaginary part of the wavelet. Therefore, a convolution with both phases produces a complex coefficient.

4. _ specifies the radius of the Gaussian. This parameter is usually proportional to the wavelength.

5. _ specifies the aspect ratio of the Gaussian. There are 80 Gabor filters and each will result in image, giving a total of 80 images. The images are then separately converted to vectors. The vectors are classified as train and test vectors. The train vectors are used to train the classifier. Test vectors are submitted to the classifier for hypothesis. The classifier uses Euclidean distance as a measure for finding match.

Algorithm: Gabor wavelet and creation of bunch graph

1. Algorithm uses manually selected landmark locations top reduce the bunch graph. The manually selected landmark locations are collected by a tool, with a graphical user interface, that allows a user to select points in an image that correspond to landmarks such as left eye, right eye, tip of the nose, left and right corner of the mouth. Save this file as landmarks file.

2. Generate Gabor wavelet with parameter as

sz_factor = 4,
lamda_param_set = {4, 4_2, 8, 8_2, 16},
Theta _set = {0, / 8 p, 2 / 8 p, 3 / 8 p, 4 / 8 p, 5 / 8 p,6 / 8 p, 7 / 8 p},
phi_param_set = {0,p/2}.
80 Gabor wavelet are generated save this file asgabor_wavelet_profile.

3. Perform convolution of each feature with Gabor filters and save coefficient (jet) in file FV_file. Gabor jets, in this case referred to as model jets. The jets are extracted from images with manually selected landmark locations. A bunch graph is created by collecting model Gabor jets for every facial landmark. The model jets are then collected in a data structure called a bunch graph. The bunch graph has a node

for every landmark on the face. Every node is a collection model jets for the corresponding landmark. The bunch graph serves as a database of landmark descriptions that is used to locate landmarks in novel imagery.

4. Gabor wavelet algorithm computes the similarity of two images. After the algorithm has created a face graph for two images, their similarity can be computed. Gabor jets are compared using Euclidean distance.

V. GABOR WAVELET + GRAPH ISOMORPHISM (COMBINED)FACE RECOGNITION ALGORITHM

1. Read the feature vector file FV_file and graph fileFV_graph_file.

2. Train vectors first by FV_file and then by FV_graph_file.

3. Give the test vector to the classifier. Classifiercompares 2 vectors and chooses minimum Euclideandistance as a measure for recognition

VI. Brightness Normalization Algorithm (B Norm)

The face images captured at different times or positions often have different brightness. These commonly affect there cognition significantly. In order to reduce the affection of the brightness, we used brightness normalization method to let the image have the same mean and the same variance value which is as follows.

1. Mean center the pixel values in the source image.

2. Linearly smooth the edges of the source image across a30 pixel border.

3. Normalize the contrast of the new image with histogram equalization.

The edge of the image is smoothed to reduce its effect infrequency space. Pixels greater than 30 pixels apart from the edge are not modified. These smoothies the image edge from actual pixel values in the center of the image to zero at the edge of the image. The algorithm then performs contrast and brightness normalizations.

VII. EXPERIMENTAL RESULTS

To verify the proposed algorithm, it was implemented and experiments were conducted. In the experiments, original images of ORL database were used. Figure 2 shows experimental result of feature selection. Figure 3 shows result of x and y coordinates for selected features. Figure 4shows result of face graph creation. Figure 5 shows preprocessing result. Figure 6 shows result of brightness normalization. Figure 7 shows adjacency matrix. Figure 8shows 80 Gabor wavelet. Algorithm used 400 images of 40persons. In the experiments, first normalized the image by the method presented in this paper. Then, to demonstrate that the normalization algorithm can really improve the face recognition rate, we carried out comparison experiments of face recognition with and without face normalization. The face images were trained and recognized based on method of graph isomorphism and Gabor Wavelet + graph isomorphism face recognition method. Algorithm used 1 to10 images of a person to train and used the other remaining as well as all images for testing. The correct recognition rate of graph isomorphism is given in table 1 and recognition rate of graph isomorphism+ Gabor wavelet is given in table 2. The tables result can prove that graph isomorphism+ Gabor wavelet+ B NORM can improve the recognition rate of face images.

VIII. CONCLUSION

This paper presented a novel algorithm for face recognition which combines graph isomorphism technique and Gabor wavelet. Algorithm was implemented and its performance was verified, which demonstrated that this method can be effectively used along with brightness normalization to improve recognition rate.

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Figure 2 feature selection

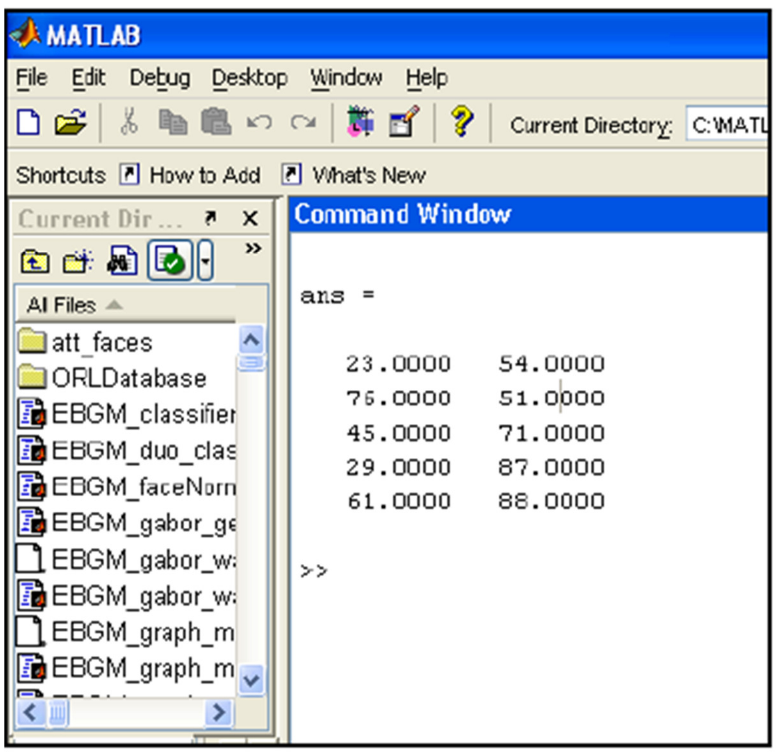

Figure 3 storing x, y coordinates.

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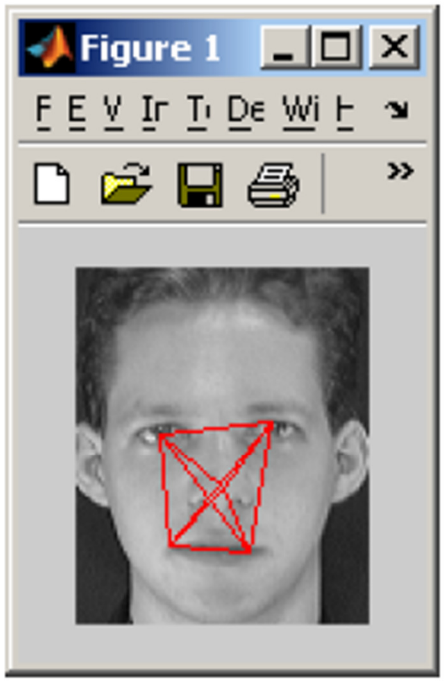


Figure 4 face graph creation.

```
Command Window
>>

temp =

  1.0e-006 *

        0    0.3349    0.2495    0.3339    0.4411
   0.3349         0    0.2453    0.4796    0.3954
   0.2495    0.2453         0    0.2354    0.2048
   0.3339    0.4796    0.2354         0    0.2384
   0.4411    0.3954    0.2048    0.2384         0
```

Figure 5 adjacency matrix.

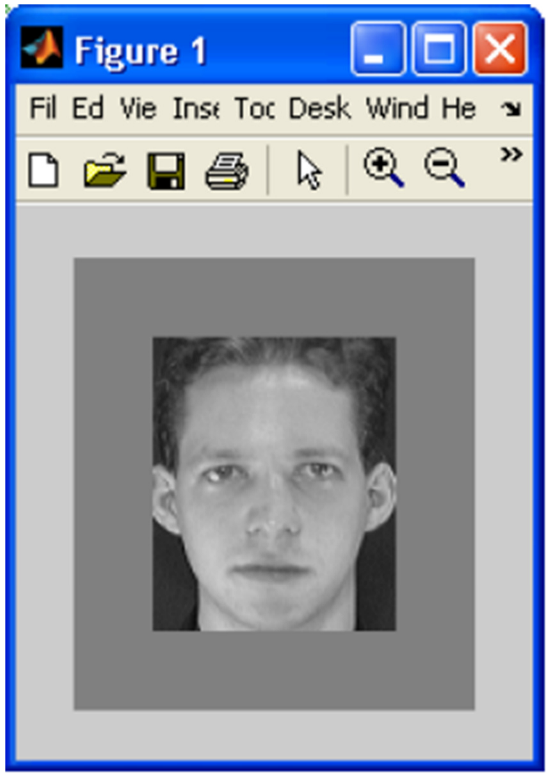


Figure 6 preprocessing face image.

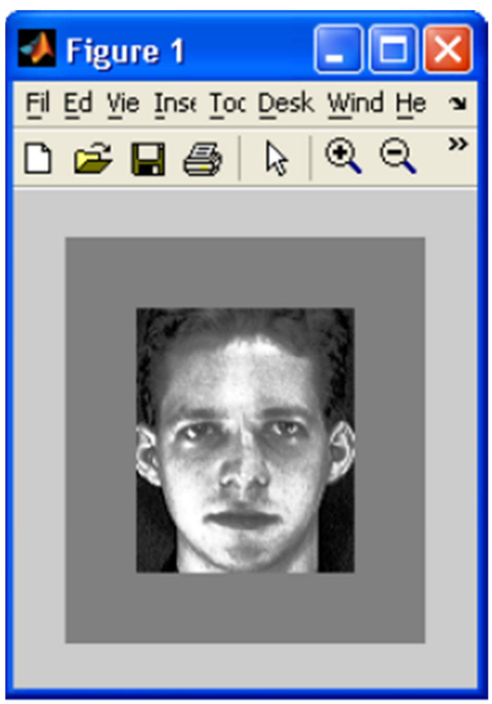
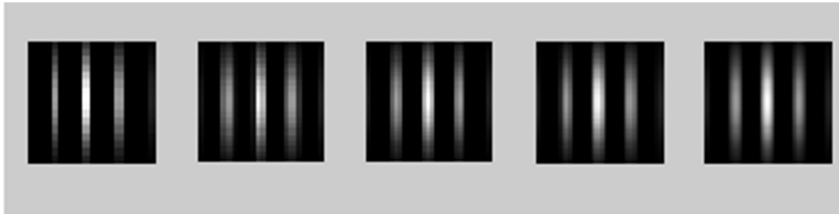


Figure 7 the result of brightness normalization.



_=0, _=0, _=4,4R2, 8, 8R2, 16.

_=0, _= /8, _=4,4R2, 8, 8R2, 16.

_=0, _=2/8, _=4,4R2, 8, 8R2, 16.

_=0, _=3/8, _=4,4R2, 8, 8R2, 16.

_=0, _=4/8, _=4,4R2, 8, 8R2, 16.

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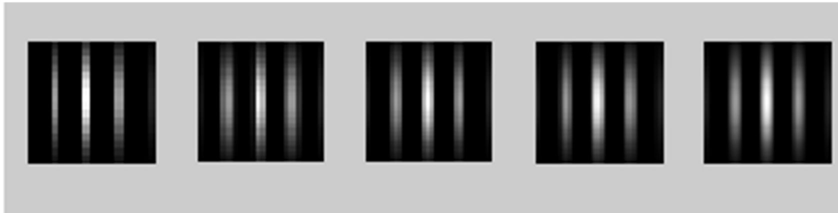
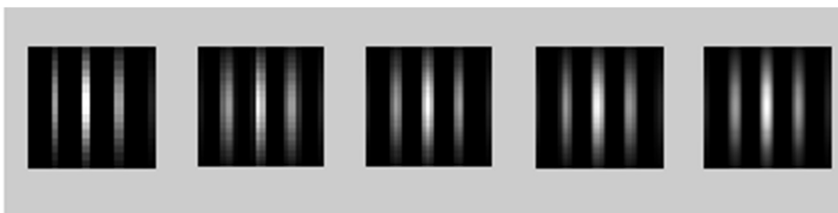


_=0, _=5/8, _=4,4R2, 8, 8R2, 16.

_=0, _=6/8, _=4,4R2, 8, 8R2, 16.



_ =0, _=7/8, _=4,4R2, 8, 8R2, 16.

_ = /2, _=0, _=4,4R2, 8, 8R2, 16.

_ = /2, _= /8, _=4,4R2, 8, 8R2, 16.

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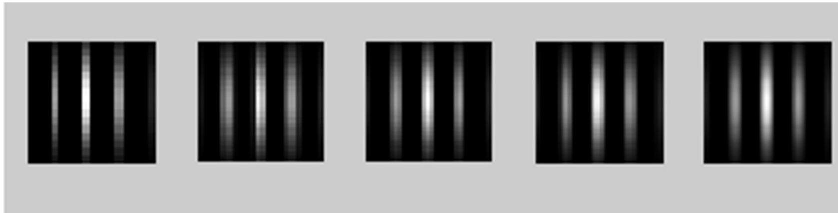
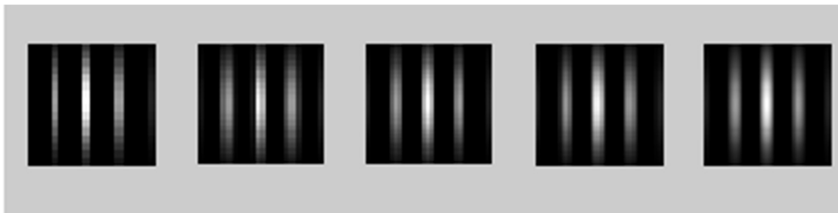


_ = /2, _= 2/8, _=4,4R2, 8, 8R2, 16.



_ = /2, _= 3/8, _=4,4R2, 8, 8R2, 16.

_ = /2, _=4/8,,_=4,4R2, 8, 8R2, 16.

_ = /2, _= 5/8, _=4,4R2, 8, 8R2, 16.

_ = /2, _= 6/8, _=4,4R2, 8, 8R2, 16.

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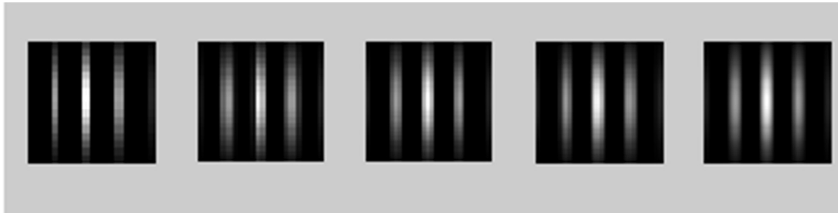

_ = /2, _= 7/8, _=4,4R2, 8, 8R2, 16.

Figure 8 80 Gabor wavelet

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TABLE I. RECOGNITION RATIO IN PERCENTAGE FOR VARIOUS FACE RECOGNITION METHODS

Training Images, nots		1	2	3	4	5	6	7	8	9	10
Test Images only	GRAPH Isomorphism	5.27	10.12	6.07	7.91	7	7	8.75	7.5	10	--
Train + Test Images	GRAPH Isomorphism	14.75	13.5	10.75	13	12.5	13	12.25	11.50	13.50	13.25

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TABLE II. RECOGNITION RATIO IN PERCENTAGE FOR GRAPH ISOMORPHISM + GABOR WAVELET

Training Images, nots		1	2	3	4	5	6	7	8	9	10
Test Images only	Graph Isomorphism+ Gabor wavelet	14.16	23.12	23.92	31.66	35.5	36.87	41.66	45	50	--
	BNorm + Graph Isomorphism+ Gabor wavelet	25.83	23.43	32.14	40.41	42.5	45.62	44.16	48.75	47.5	--
Train + Test Images	Graph Isomorphism+ Gabor wavelet	22.75	38.5	45.5	55.75	62.75	65.25	71.5	74.75	78	82
	BNorm + Graph Isomorphism+ Gabor wavelet	33.25	38.25	51.5	61.5	66.75	73.25	74.5	79.25	80.5	85

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